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14. ABSTRACT
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Application of Symbolic Regression to Electrochemical Impedance Spectroscopy Data for Lubricating Oil Health Evaluation

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The authors have applied an advanced set of auto-regressive tools for identifying potentially complex, linear and non-linear relationships in data, wherein the underlying physical relationships are not well described. In this paper these tools and techniques are described in detail, and the results of the application of these tools to evaluation of diesel engine lubricating oil health (based on electrochemical impedance spectroscopy data) is detailed. It is demonstrated that highly accurate models can be constructed which take as input features derived from diesel engine lubricating oil electrochemical impedance spectroscopy data and output estimates of traditional laboratory based oil analysis parameters. The electrochemical impedance spectroscopy and laboratory analytical data used are from a field deployment of oil condition sensors on several long-haul class 8 diesel trucks. The dataset was divided into training and test datasets and goodness of fit metrics were calculated to evaluate model performance. Models were successfully generated for nitration, soot content, total base number, total acid number, and viscosity.

1. INTRODUCTION

An on-line oil condition monitoring device for application to vehicular diesel engines provides significant benefit over traditional oil sampling methods. The online nature of the monitoring device eliminates the long delays associated with traditional laboratory analysis and prevents the possibility of sampling errors. Knowledge of the actual condition of the oil at a particular time also allows for the real time adjustment of oil drain intervals – either extending to take advantage of additional remaining useful life or shortening to prevent engine damage due to abnormal fluid conditions or contaminations. Maintenance actions can also be planned and carried out opportunistically.

It has long been known that electrochemical impedance spectroscopy (EIS) can provide valuable insight into the condition of lubricating oils and their additive packages (Byington et al 2010, Moffatt et al 2012). In order to mature this understanding research within this field has focused on characterizing the relationship between lubricating oils and electrochemical impedance spectroscopy. Lvovich V F. and Smiechowski M. F. (2011, 2008, 2006, 2005, 2002, 2001) are the primary contributors to this characterization and have produced several well behaved models of the relationship. While these models provide tremendous insight into lubricant chemistry, they are based on empirical data from laboratory grade instrumentation and known oil formulations and contaminants. For on-line lubricant monitors, the oil formulation and contamination is unknown and therefore samples must be drawn and traditional oil analysis performed. These traditional laboratory tests typically output lubricant chemical and mechanical properties such as Total Acid Number (TAN), Total Base Number (TBN), percent soot content, viscosity, and degree of nitration, among others.

The work presented in this paper extends the scope of previous modeling research by establishing a direct map between on-line oil sensor features and the underlying oil chemistry assessed through traditional laboratory analysis. While correlations have been observed between these on-line EIS data and those values which represent the output of traditional laboratory oil analysis (Mackos et al 2008), models have not been developed to explicate this relationship. While EIS data alone can be used to generate lubricant remaining useful life estimates, using models to estimate traditional laboratory oil analysis parameters

provides additional benefits; for example, historical condemnation thresholds established using these traditional oil analysis parameters can be leveraged.

The physics of the relationship between measured electrochemical data and laboratory test outputs like TAN and TBN is vastly complex. Therefore the explicit definition of transfer functions to translate EIS data into the desired laboratory test features is difficult and impractical. Several methods exist for modeling complex scientific data. When expert knowledge of the parametric relationships between measured data are known, fixed-form models can be applied. In the case that relationships are not well understood, numerical models are often used. E.g neural networks, naïve bayes classifiers. These models however do not explain discovered relationships intuitively and thus do not easily distill data into scientific knowledge. Instead, the authors have pursued the application of symbolic regression techniques which require no a priori knowledge of the functional relationship between the inputs and desired outputs of such a model and result in a closed form solution which may describe physical and chemical relationships more clearly.

The authors have been working with US Army Tank Automotive Research, Development and Engineering Center (TARDEC) to develop next generation hardware for online oil condition monitoring. As part of this effort, and with the cooperation of the National Automotive Center, several sets of existing oil condition monitoring hardware were deployed on long haul class 8 trucks. A periodic oil sampling and laboratory analysis plan was also implemented. These laboratory analyticals and EIS data were used to evaluate the capability of symbolic regression techniques to generate models for estimating TAN, TBN, nitration, soot content, and viscosity.

2. SYMBOLIC REGRESSION OVERVIEW

The main objective of this effort was to correlate laboratory generated tribology results with sensor generated electrochemical impedance spectroscopy data. While there is prior understanding of the chemical and physical nature of oil and how it interacts with contaminants and other breakdown processes, this understanding has never directly resulted in models that correlate tribology data to EIS data. Given the ground truth information this is a supervised learning problem and since the tribology data is not discretized, a regression method is appropriate (rather than classifier methods such as logistic regression, neural networks, support vector machines, etc.). Multi-variant Linear regression is the obvious and standard method; if the specific model for optimization is known then symbolic regression is unnecessary. If however the model is unknown, the application of linear regression is a labor intensive process, to include adding and subtracting features, increasing and decreasing the complexity of features included, cross-validation, and regularization. The application of Symbolic Regression, and the toolsets which were employed, effectively automate these processes. Symbolic regression also provides significant benefit over linear regression when the ultimate goal is to deploy the models in an embedded environment. Like linear regression a closed form equation is generated, however the operations for inclusion in the solutions identified can be defined ahead of time; in this manner any limitations of the embedded platform can be accounted for. Solutions of varying levels of complexity can also be generated and evaluated to trade off performance in terms of accuracy and computational complexity.

The Symbolic Regression algorithm described in this section is used to identify general and potentially complex relationships, in this case between the online oil-condition monitor observations and associated laboratory generated oil chemical and mechanical properties. The Symbolic Regression algorithm (Koza, 1992) is a generalization to the standard regression problem formulation in that it requires very few assumptions regarding the underlying regression model and the output of the algorithm is a closed form expression that can easily be implemented on an embedded platform. The produced closed form expressions can be non-linear and have temporal dependencies and as a result important information such as leading fault (temporal) or cyclic degradation (non-linear) can be identified using this technique. In short, the Symbolic Regression technique is an excellent choice when faced with complex problems where many of the underlying physical behaviors of a system are not well described.

The Symbolic Regression tool used for this analysis relies on Genetic Programming (Koza, 1998) to search for the best functional/algebraic map between the produced oil condition monitor features and the oil analysis results reported by the laboratory. The Genetic Programming algorithm evaluates a pool of symbolic expressions represented by a collection of parse trees (one such tree is depicted in Figure 1) and iteratively applies candidate selection, cross-over and mutation operations to generate the most effective expressions. The fitness of each expression can be evaluated using many different metrics; however, for the analysis performed in this work, the mean absolute error was used. As with most data driven modeling tools, special attention must be paid to avoid over-fitting the derived model to the provided data. For Symbolic Regression the over-fitting problem is addressed at two different levels. First, the algorithm provides a Pareto front of optimal solutions that allows the researcher to select the ideal solution in terms of functional complexity and performance. For instance, if a simple solution performs only slightly worse than a much more complex expression, the Symbolic Regression tool will provide both solutions to the researcher who can then select the correct solution in terms of complexity and performance. By providing this

functionality, it is possible to eliminate overly complex expressions that tend to be highly tuned to the training data. The second technique used to prevent over-fitting is the standard cross-validation approach. That is, the generated expressions are optimized to fit a training set, say 80% of the original data, but when evaluating the performance of the expressions the remaining 20% of the data is used. This simple approach reduces the likelihood of over-fitting.

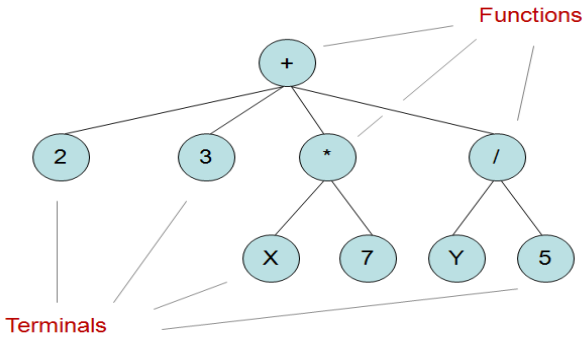

Figure 1. An example of a parse tree corresponding to the expression 2+3+x*7+Y/5.

In addition to the ease of implementing the derived expressions on an embedded platform, it is also possible to analyze the individual terms in each of the expressions to determine what their impact may be on the overall model response. This sensitivity analysis step provides insight into how important each term is, and also into what features should be generated by the oil condition monitor.

It is worth noting that the Symbolic Regression analysis is only performed during the development of the oil assessment model. That is, the symbolic regression process will not be running on the sensor itself; only the functional output of the symbolic regression process would be considered for embedded implementation. It should also be noted that Symbolic Regression analysis tools are freely available to developers through the Eureqa software developed by a group of researchers at Cornell University (Schmidt & Lipson, 2009). This tool is mature and allows users to distribute the search task over a large number of computers through Amazon Cloud Services http://aws.amazon.com/.

3. Application To Diesel Engine Lubricating Oil

3.1. Description of the Dataset Used

The underlying technology for the oil condition monitor detailed herein is electrochemical impedance spectroscopy (EIS), wherein the fluid under test is subjected to a dynamic electrical signal and the fluid's effects on the signal are measured and correlated to various chemical and physical phenomena. The oil condition monitor's embedded algorithm trends temperature-normalized and filtered electrochemical impedances measured at a high frequency (HF), medium frequency (MF), and low frequency (LF).

As previously described, a field deployment on several long haul class-8 trucks was used to generate the necessary EIS and laboratory analytical data for this effort. Across these installations, online oil condition monitoring devices collected data continuously for several months, resulting in a dataset which spanned more than ten oil changes.

Throughout most of the test period, oil samples were taken from the vehicles and sent to a third party laboratory for analysis. Three of the trucks in the installation were selected for inclusion in the symbolic regression study based on the quality and consistency of their corresponding data sets.

In the following section, the output of the models generated through the application of the previously described symbolic regression techniques are presented against laboratory analytical data for comparison.

3.2. Symbolic Regression Results

Symbolic regression models were created for the following laboratory generated analyticals: nitration, TBN, TAN, Soot and viscosity. These models are represented by closed form mathematical expressions suitable for implementation in embedded hardware. An example of the kind of expressions that comprised these models is given in Eq. (1) below, wherein *Feature 1* is one of the electrochemical features generated by the oil condition monitor and *X*, *Y*, and *Z* are constants.

$$\boldsymbol{TBN\ est.} = \mathbf{log}(\textit{Feature 1} - \boldsymbol{XeY}) - \boldsymbol{Z} \quad (1)$$

To ensure that the model did not over-fit the data the model performance metrics were computed by performing cross-validation using 50% of the data. For each laboratory analytical a single model was created based on data from all of the trucks so that the repeatability of the model across different oil condition monitoring hardware and different vehicles could be evaluated.

In Figure 2 below, the model based Nitration estimate is represented by black data points. The vertical lines indicate when an oil change occurred. As expected, the nitration level dropped after each oil change. The squares indicate the nitration measurement made off-line through laboratory analysis using oil samples drawn from each truck during the test. The squares are plotted along the x-axis according to when the sample was drawn. Also note that more online EIS results have been acquired than laboratory analytical data at the time of writing of this paper. This is especially the case for truck 3, for which oil samples have not yet been received for operation after Jan 21st.

The model performs well across all three trucks and across the entire test. The only laboratory measurement that did not line up well with model results was the first sample drawn in March on truck 1. It is more likely that the laboratory

measurement is wrong rather than the sensor model estimate since it is unlikely that the nitration level increased, decreased and increased again across one oil cycle; this is not typical of nitration trending. The sensor installed on truck 2 also underestimated nitration on the fifth oil cycle.

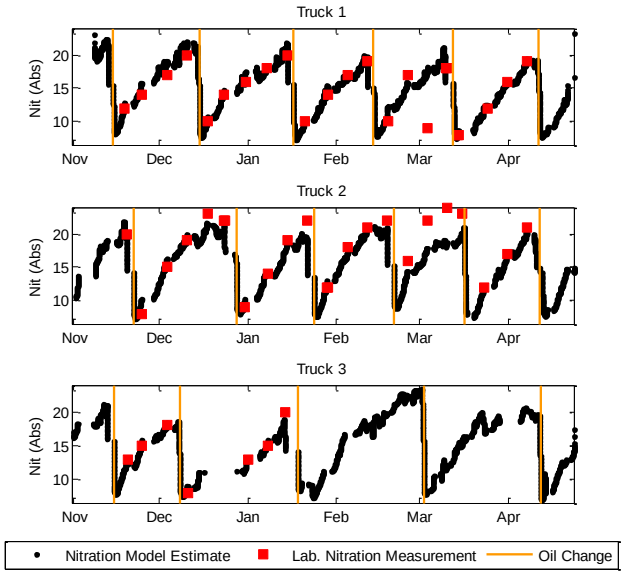

Figure 2: Nitration estimate plotted with Lab Nitration Measurements

Statistical results are summarized in Table 1 and a histogram of the differences between the model predicted values and the ground truth is depicted in Figure 3.

Standard Deviation of the Residual	1.7934 (Abs)
Mean of the Residual	-0.0380 (Abs)

Table 1: Nitration Model Performance Metrics

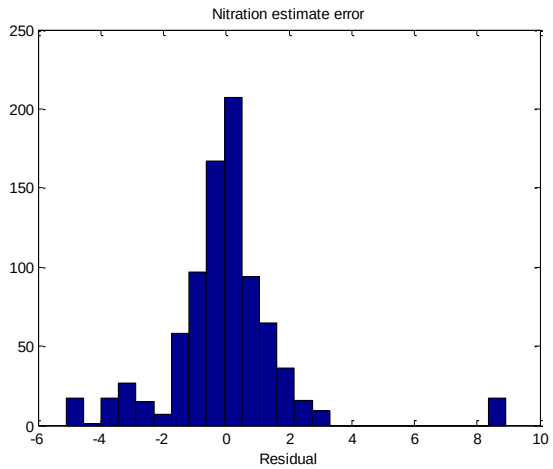

Figure 3: Histogram capturing error between the model generated Nitration value and the laboratory results

The model appears to perform well given that the Nitration values observed in the laboratory data ranged from 6 to 24 (Abs). That is, the standard deviation of the modeling error is 9.9% of the range of the laboratory measurements.

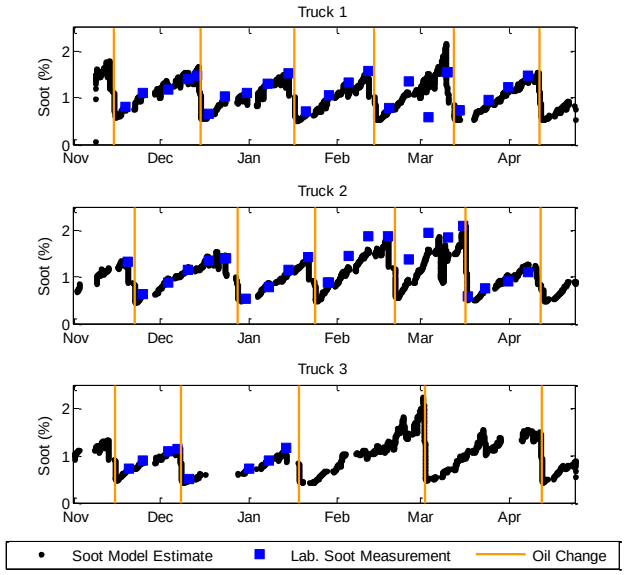

Figure 4: Soot estimate plotted with Lab Soot Measurements

Figure 4 shows the results from the same data set but applying the soot estimation model and comparing with laboratory soot measurements.

The model performs well across all three trucks and across the entire test. The first sample drawn in March on truck 1 continues to line up poorly with inline data. This means it is most likely due to a misrepresentative oil sample being drawn / analyzed. The sensor installed on truck 2 also underestimated soot content on the fourth oil cycle.

The statistical results are summarized in Table 2 and a histogram of the differences between the model predicted values and the ground truth is depicted in Figure 5.

Standard Deviation of the Residual	0.0722(%)
Mean of the Residual	-0.1373 (%)

Table 2: Soot Model Performance Metrics

The model appears to perform well given that the Soot values observed in the laboratory data ranged from 0.5 to 2 (%). That is, the standard deviation of the modeling error is 4.5% of the range of the laboratory measurements. Based on this observation, the soot estimation model was the highest performer among the 5 models calculated.

Figure 6 shows the results from the same data set but applying the TBN estimation model and comparing them with laboratory TBN measurements.

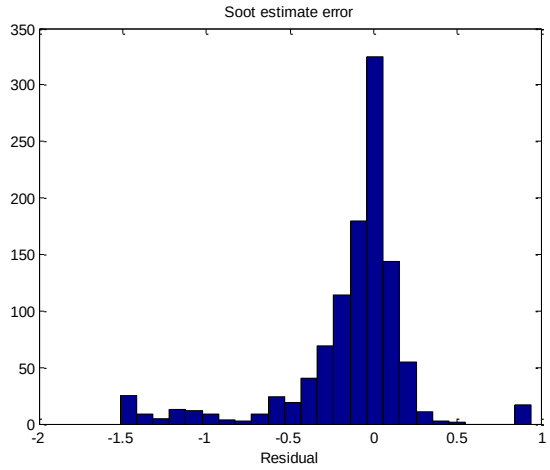

Figure 5: Histogram capturing error between the model generated Soot value and the laboratory results

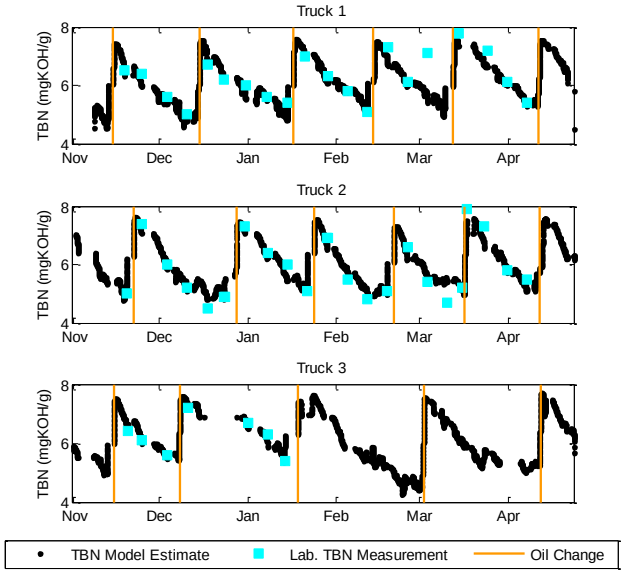

Figure 6: TBN estimate plotted with Lab TBN Measurements

The model performs well across all three trucks and across the entire test. There are a greater number of extreme outliers than the Soot and Nitration models produce but still a healthy performance within one standard deviation as is shown in Table 3 below.

Standard Deviation of the Residual	0.3220 (mgKOH/g)
Mean of the Residual	-0.1940 (mgKOH/g)

Table 3: TBN Model Performance Metrics

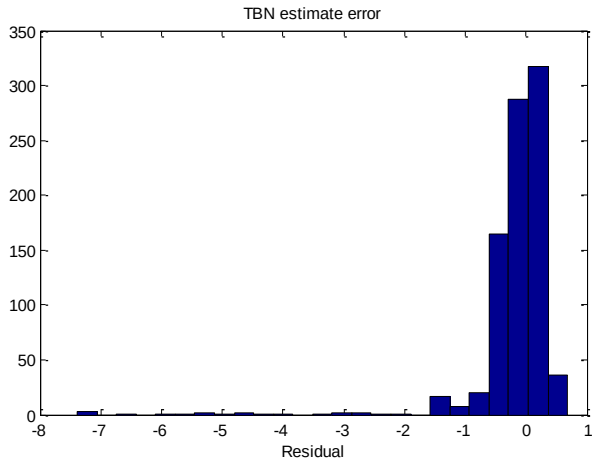

Figure 7: Histogram capturing error between the model generated TBN value and the laboratory results

Given that the TBN values observed in the laboratory data ranged from 2.8 to 7.9 (mgKOH/g), the standard deviation of the modeling error is still only 6.3% of the range of the laboratory measurements. Therefore while there are a greater number of residual outliers than Nitration for example, it still out performs the Nitration model the majority of the time.

Figure 8 shows the results from the same data set but applying the TAN estimation model and comparing with laboratory TAN measurements.

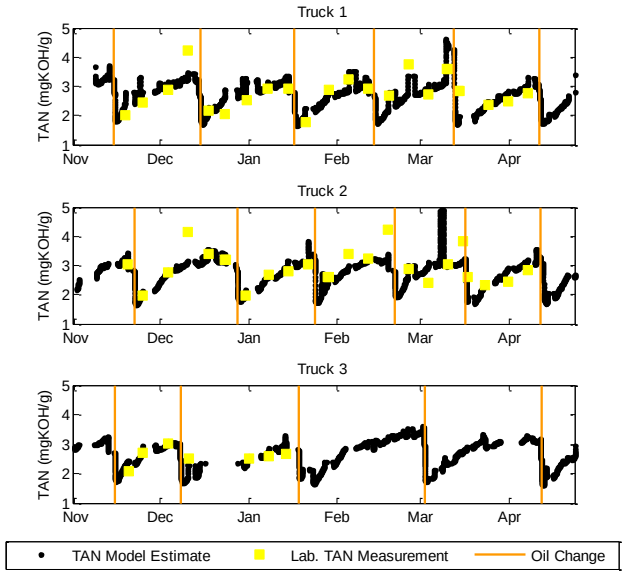

Figure 8: Soot estimate plotted with Lab. Soot Measurements

TAN appears to be the worst performer of the five models created. However the model does appear to show a correlation. The statistical performance shows that the model does not perform well enough to be relied upon.

Standard Deviation of the Residual	1.2993 (mgKOH/g)
Mean of the Residual	0.5829 (mgKOH/g)

Table 4: TAN Model Performance Metrics

Considering that the laboratory data ranged from 1.79 to 4.22 (mgKOH/g), the standard deviation of the modeling error is over 50% of the range of laboratory measurements. In other words the confidence bounds of the estimate extend to over half the range of typical data.

Finally, Figure 10 shows the results from the same data set but applying the Viscosity estimation model and comparing with laboratory Viscosity measurements.

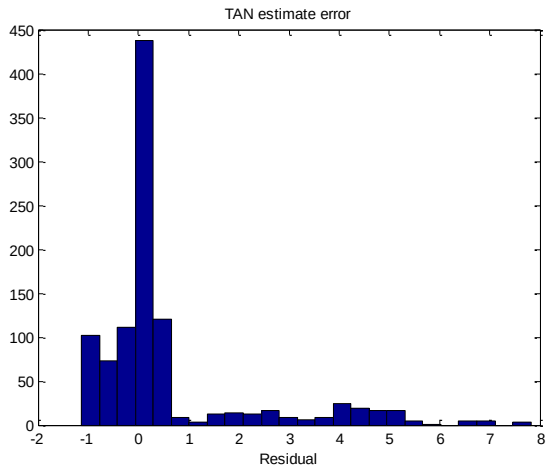

Figure 9: Histogram capturing error between the model generated TAN value and the laboratory results

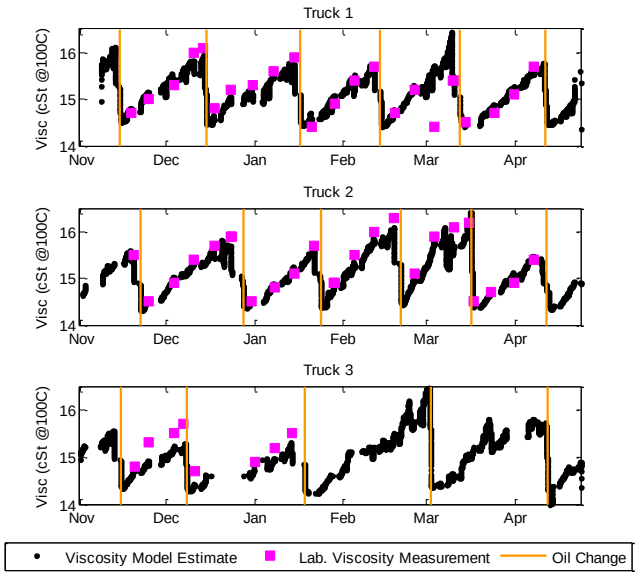

Figure 10: Viscosity estimate plotted with Lab. Viscosity Measurements

The model performs well across all three trucks with perhaps a slightly weaker performance implemented on truck 3 data. The statistical results are summarized in Table 5 and Figure 11.

Standard Deviation of the Residual	0.1188 (cSt @100C)
Mean of the Residual	-0.0673 (cSt @100C)

Table 5: Viscosity Model Performance Metrics

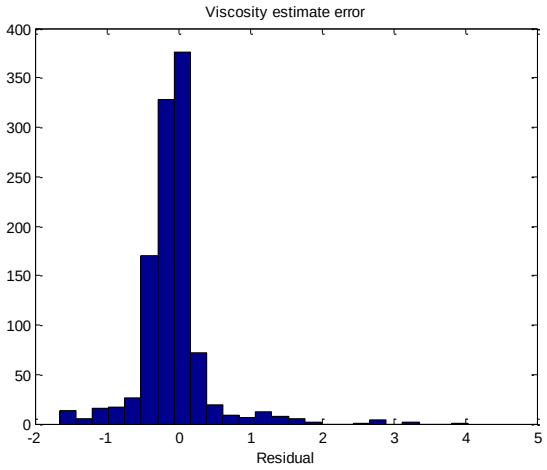

Figure 11: Histogram capturing error between the model generated Viscosity value and the laboratory results

The model appears to perform well given that the Viscosity values observed in the laboratory data ranged from 14.4 to 16.3 (mgKOH/g). That is, the standard deviation of the modeling error is 6.3% of the range of the laboratory measurements.

3.3. RUL Estimation Plan

The data shown in Figure 2, Figure 4, Figure 6, Figure 8 and Figure 10 can be reconditioned to display the features vs. hours on oil by identifying top-ups and oil changes and adjusting the time on oil accordingly. The resulting reconditioned data for Nitration, Soot, TBN and Viscosity estimates are shown from Figure 12 through Figure 15. The bands of data are represented by a family of feature curves. The traditional oil analysis results are also plotted on each plot as colored squares. Each deterministic curve, after filtering for noise, is monotonically increasing and can be fitted to a general function form, n^{th} order or exponential, depending on the feature type. As one can readily see, while there is significant spread of the values, the trend on each is clear and a regressive model can be used to predict a future threshold exceedence on any parameter.

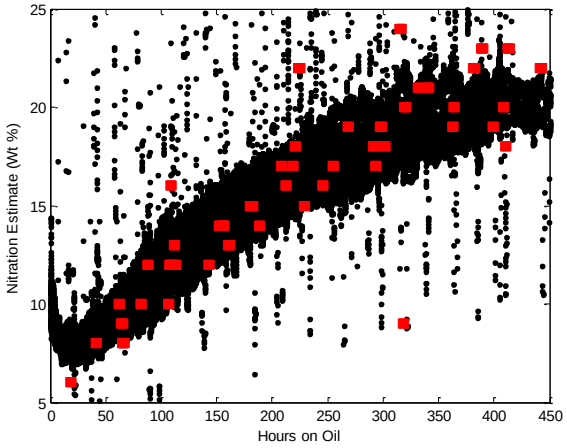

Figure 12: Hours on Oil vs. Nitration Estimate

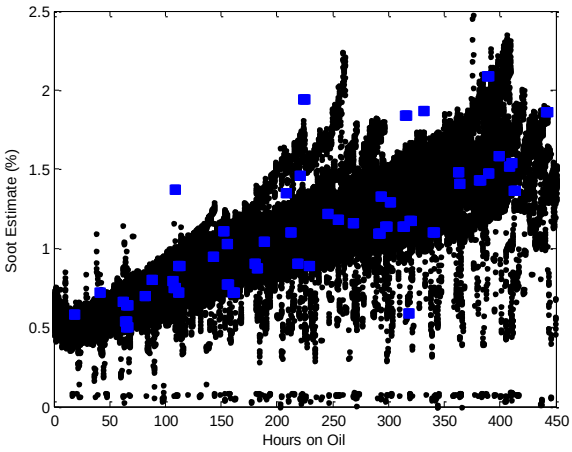

Figure 13: Hours on Oil vs. Soot Estimate

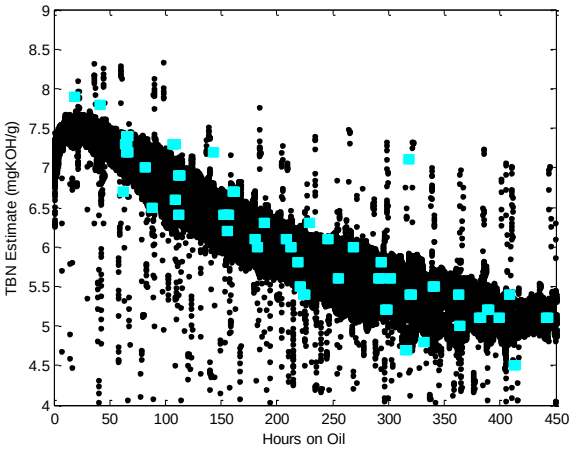

Figure 14: Hours on Oil vs. TBN Estimate

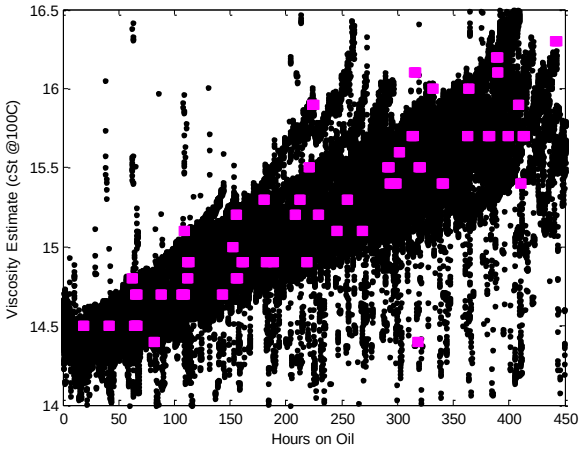

Figure 15: Hours on Oil vs. Viscosity Estimate

Given the nature of the data and in order to better approximate the uncertainty band for each considered feature, a Monte Carlo method was chosen to estimate remaining useful life probabilistic outputs. The approach starts with identifying the core parameter drivers of the model and assigning an initial distribution to each variable. The drivers can be identified by performing a sensitivity analysis to quantify the influence of a parameter with respect to the probabilistic outputs, such as the remaining useful life distribution. A Monte Carlo simulation is then performed and consists of randomly sampling from the initial distributions and running the models into the future over a predefined operating profile.

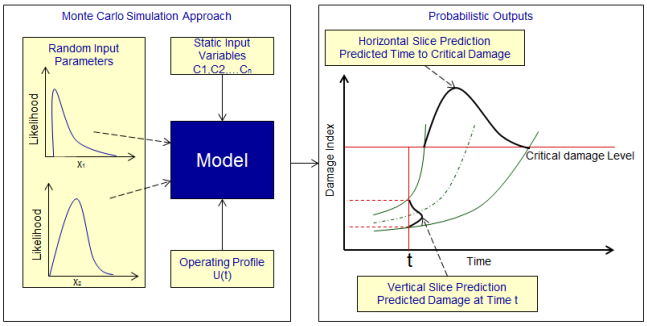

Figure 16: Monte Carlo Probabilistic Method

Figure 16 is an illustration of the approach. By sampling the initial parameter distribution, a family of model curves is generated and can be used to calculate vertical or horizontal slice predictions. A horizontal slice is generally taken at the critical damage level and will generate a distribution on time to critical damage which also represents the remaining useful life probabilistic output. A vertical slice is taken at any point in time and represents a distribution on predicted damage at specified time *t*.

It was also determined to limit the number of input parameter distributions to three or less. The more distributions are being sampled from, the more simulations are needed to obtain a better approximation on the uncertainty spread. Different sampling methods, such as importance sampling, can be applied to reduce the simulation time and still output a reasonable approximation of the spread.

One of the advantages of this approach is the ability to optionally update the initial input distributions given ground truth information. The underlying assumption is that if the module has access to accurate oil analyticals, these results can be used to update the initial distributions. By producing more accurate initial conditions for the prognosis model, the system is capable of improving the subsequent prognosis results.

The RUL determination is a direct adaptation of the authors prior work in health-based prognostics. The prior demonstrated method uses Particle Filters to perform feature trend predictions (Zhang et al., 2008). Particle filtering is an application of Bayesian state estimation that calculates an a posteriori probability density function (PDF) of a state of a system based on a priori observations or measurements. If the calculation of the future state of the system is extended in multiple steps with the use of a model, the particle filtering algorithm can perform long term predictions. In this case, the system observations are initially used to build a PDF of the "present" or "current" system condition, as illustrated conceptually in Figure 17.

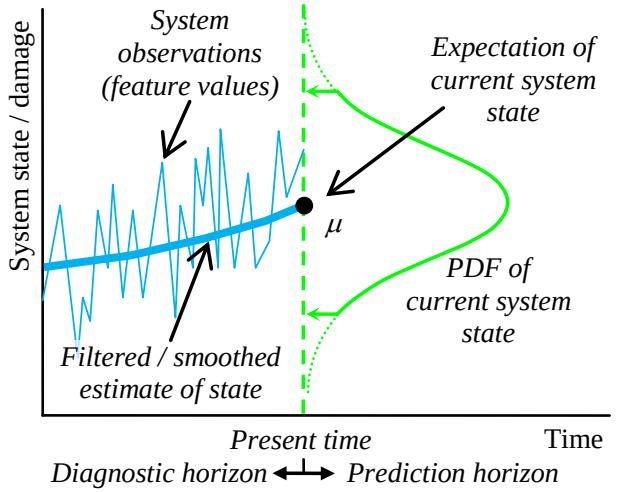

Figure 17. Determination of the state of a system as a PDF based on feature values

This PDF is then sampled into "particles" representative of potential system states with individual weights. Using the model, the prognostic algorithm simulates the progression of the weights in time to do a prediction of possible future system states, as illustrated in Figure **18**.

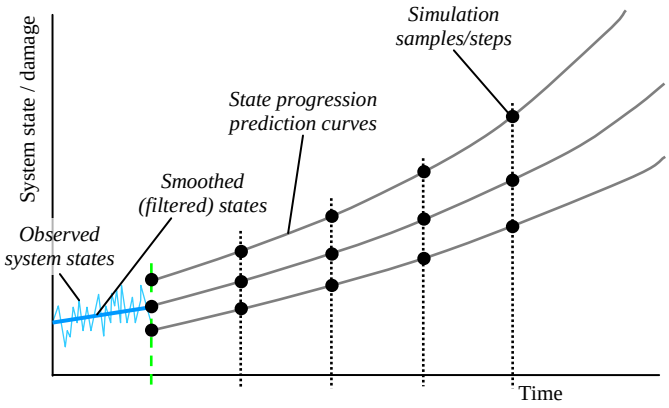

Figure 18. System state prediction and progression curves

Just as with the initial state, future states of the system can be represented by PDFs. Once the progression of the system state has been determined, the algorithm can be used to predict the time required for the system to reach a condition of interest, such as a need for maintenance. The condition predicted is represented by a "prediction threshold" line. Because there is uncertainty in the future system states (as represented by the different state progression curves), there is also uncertainty in the predicted time to reach the threshold. This uncertainty in time is represented also by a PDF, referred to as the "time-to-threshold" (TTT) PDF. The definition of prognostic confidence is tied to how the area of the TTT PDF is divided. To determine the minimum time remaining to reach the prediction threshold, called the "just-in-time" point, a confidence specification is required. Figure **19** illustrates how a 95% prediction confidence is used to determine the just-in-time point. This approach has been successfully used in a range of different mechanical and electrical prognosis problems.

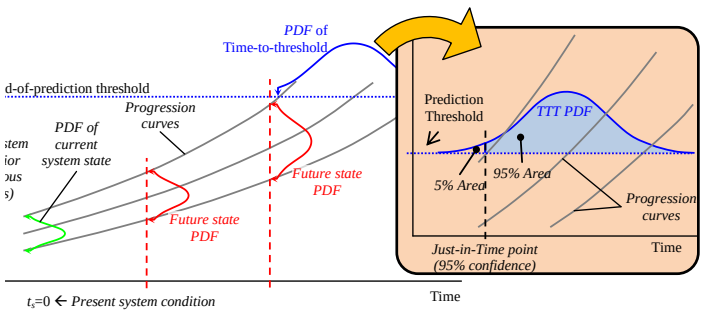

Figure 19. Determination of the prediction time to reach a prognostic threshold with a given prognostic confidence (the inlay box provides an example using 95% confidence)

4. CONCLUSION

Of the five models created, all but one performed well enough for embedded implementation in a next generation

online oil condition monitor, with the highest performing estimate being soot estimation, and TBN and Viscosity models a close second.

It should be noted however that the laboratory data ranges mentioned for each analytical also represent boundaries within which the model can be implemented. If, for example, soot content extends above 2%, the model can no longer be trusted to perform with the stated accuracy. Once data is acquired outside the range of this data set, the models can be matured to handle the increased range and the performance of the model will have to be reassessed.

Another limitation of the model is the singular oil type in use during this field trial. To remove potential installation or vehicle specific artifacts contained in the models they will need to be verified against more diverse data sets.

Lastly the approach and framework has been offered to extend this regressive analysis approach to perform real-time prediction of oil RUL. Several specific methods were offered to handle the uncertainty and also produce a useful prediction in automated software. Realization of this technology will not only allow for improved equipment protection and enhance the underlying oil-wetted component effective reliability with its ability to look for contaminants and aging/wear out mechanisms, but it will also allow both oil sampling/lab tests and oil changes to be performed on a predictive condition-based schedule. Thus, this technology has the ability to provide significant return of value to the operator and maintainer as well as provide environmental/green movement benefits with the reduction in oil usage and subsequent disposal.

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NOMENCLATURE

EIS	Electrochemical Impedance Spectroscopy
TAN	Total Acid Number
TBN	Total Base Number
TARDEC	Tank Automotive Research, Development and Engineering Center

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